

Lawrence Berkeley National Laboratory

Recent Work

Title

Evaluating the economic return to public wind energy research and development in the United States

Permalink

<https://escholarship.org/uc/item/6sp765x3>

Authors

Wiser, R
Millstein, D

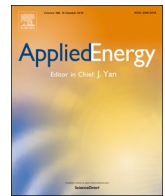
Publication Date

2020-03-01

DOI

10.1016/j.apenergy.2019.114449

Peer reviewed



Evaluating the economic return to public wind energy research and development in the United States

Ryan Wiser*, Dev Millstein

Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

HIGHLIGHTS

- The U.S. government has invested \$3 billion in wind research since 1976.
- Analysis demonstrates sizable, positive returns on this past wind research.
- Net benefits equal \$31.4 billion, leading to an 18 to 1 benefit-to-cost ratio.
- Avoided carbon dioxide emissions are estimated at 1510 million metric tons.
- Alternative methods & assumptions yield benefit-to-cost ratios of 7-to-1 to 21-to-1.

ARTICLE INFO

Keywords:

Wind power
Research and development
Benefit-cost analysis
U.S. Department of Energy
Levelized cost of energy
Learning curve

ABSTRACT

The U.S. government has invested in wind energy research since 1976. Building on a literature that has sought to develop and apply methods for retrospective benefit-to-cost evaluation for federal research programs, this study provides a quantitative analysis of the economic social return on these historical wind energy research investments. Importantly, the study applies multiple innovative methods and varies important input parameters to test the sensitivity of the results. The analysis considers public wind research expenditures and U.S. wind power deployment over the period 1976–2017, while also accounting for the full useful lifetime of wind projects built over this period. Assessed benefits include energy cost savings and health benefits due to reductions in air pollution. Overall, this analysis demonstrates sizable, positive economic returns on past wind energy research. Under the core analysis and with a 3% real discount rate, the net benefits from historical federal wind energy research investments are found to equal \$31.4 billion, leading to an 18 to 1 benefit-to-cost ratio and an internal rate of return of 15.4%. Avoided carbon dioxide emissions are not valued in monetary terms, but are estimated at 1510 million metric tons. Alternative methods and input assumptions yield benefit-to-cost ratios that fall within a relatively narrow range from 7-to-1 to 21-to-1, reinforcing in broad terms the general finding of a sizable positive return on investment. Unsurprisingly, results are sensitive to the chosen discount rate, with higher discount rates leading to lower benefit-to-cost ratios, and lower discount rates yielding higher benefit-to-cost ratios.

1. Introduction

Technological innovation has played a pivotal role in past transformations of the energy supply system, leading to major shifts in the primary sources of energy and enabling the provision of energy services at affordable levels despite enormous growth in demand [1]. Further innovation is crucial if these trends are to continue, especially if ambitions for decarbonization are to be realized (e.g., [2]). For many years, there have been calls for increased public research and development (R&D) in the energy sector (e.g., [3,4,5]). Privately funded R&D

is limited by the market failure whereby companies carrying out R&D incur the full costs of their efforts but cannot capture the full benefits because of spillovers to other firms [6,7]. Therefore, publicly funded R&D is justified as a means to counteract this market failure.

The response to these calls for increased publicly funded energy R&D has been tepid to date—R&D has not expanded dramatically over the past several decades. In part, this may be due to uncertainty about the economic return to these investments, along with concerns that past public R&D efforts have not always realized their full desired potential [8,9]. Quantitative evaluations of historical R&D investments are rare,

* Corresponding author.

E-mail address: rhwiser@lbl.gov (R. Wiser).

<https://doi.org/10.1016/j.apenergy.2019.114449>

Received 23 July 2019; Received in revised form 20 December 2019; Accepted 22 December 2019

0306-2619/ © 2019 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

and even the methods that might be employed to conduct such evaluations remain underdeveloped. Policymakers may be understandably hesitant to increase R&D expenditures when the past return on investment is unclear.

This paper partially addresses these information gaps by quantifying the economic social return on the U.S. Department of Energy's (DOE's) historical wind energy R&D investments. Wind energy has expanded rapidly in recent years, both globally [10] and in the United States [11]. This expansion has been enabled by technological advancements since the 1970s that have dramatically increased the scale and sophistication of wind turbines and plants, yielding sizable reductions in the cost of wind energy [12,13,14]. Wind energy also holds potential for substantial continued expansion, but the degree of growth will be dictated in part by additional technical advancements and further cost reductions [15,16,17]. To date, wind energy has been a significant target for public R&D expenditure. The U.S. federal government, through the DOE, has been the largest source for such funding, investing in wind energy R&D since 1976 with total expenditures (in real 2017\$¹) of \$3.0 billion through 2017. This \$3.0 billion represents roughly one third of all publicly funded wind R&D worldwide over this period, based on data from IEA [18].

This paper both analyzes the economic social return on DOE's wind energy R&D expenditures from 1976 to 2017, and assesses the sensitivity of the findings to various methodological choices and input assumptions. The core approach used in this program-level impacts analysis builds on a literature that has sought to develop and apply methods for retrospective benefit-to-cost evaluation for U.S. federal R&D programs, including NRC [19], Pelsoci [20], and Ruegg et al. [21]. The basic analytic framework for retrospective R&D assessments recommended by all of these reports assumes that advancements generated by the public sector would have been accomplished by the private sector alone, but with a delay. The methods and assumptions used in this paper are broadly consistent with the earlier work, while improving on previous methods with more-accurate data. As points of comparison, two alternative approaches for estimating the economic return on DOE's wind energy R&D investments are employed, in one case building on the learning curve literature. In addition, the sensitivity of the results to a subset of the core input assumptions is tested. The alternative methods and sensitivity analyses enhance confidence in the core findings.

This work complements past efforts to evaluate the impacts of DOE's wind energy R&D, and it may inform more-comprehensive future assessments. Past work to independently evaluate aspects of the performance of DOE's wind R&D efforts includes Pelsoci [20]—the most recent previous program-level benefit-to-cost evaluation. Ruegg and Thomas [22] sought to clarify if, how, and to what extent others have used knowledge-based outputs from DOE's wind R&D to further the commercial development of wind energy. Navigant [23] assessed DOE's Wind Powering America program, the goal of which was to educate, engage, and enable stakeholders to make informed decisions about wind energy deployment.

This paper makes two key contributions to the broader literature. First, the paper adds to a global literature that has sought to elucidate the impacts of public wind R&D. Several studies have *qualitatively* examined the successes and challenges of different models for wind R&D (e.g., [24,25,26]), without attempting to estimate quantitative measures of the net return on investment. Other work has been more quantitative, seeking to disentangle the relative impacts of R&D and deployment-oriented learning on the historical cost of wind (e.g., [27,28]), but it has stopped short of translating cost reductions into measures of the economic return to R&D investments. The work presented in this paper seeks to fill these literature gaps by quantitatively

assessing the economic return on historical wind R&D. More broadly, this work also contributes to a literature that seeks to quantify the benefits and costs of historical public R&D investments, whether focused on wind or not. It does so, in part, by illustrating the application of and improvements to a long line of related work that has focused on energy R&D in the United States. In addition, by comparing the core results of the analysis with those generated from an innovative new method that extends two-factor learning curves (2FLCs), this paper highlights one means of validating or at least enhancing confidence in the results of historical R&D assessments.

The remainder of the paper is structured as follows. The next section highlights the data and methods used in this analysis, both for the core method and the two supplementary approaches. The results of the analysis are then described. The paper ends with a summary of key findings, along with recommendations for further research to extend the work presented here.

2. Methods, data, and past research

The methods, assumptions, and data that underlie the analysis are summarized in this section. Key literature on which the current analysis builds is also highlighted. First, the core approach is described, starting with a basic overview of the method applied and the previous literature that has used similar approaches. The Pelsoci [20] study is then described, because it represents the most recent program-level analysis of DOE's wind energy R&D investments. With that as background, the approach taken in this study to build on the previous literature is summarized. Emphasis is placed on comparing the assumptions and approaches used in this study to those used in Pelsoci [20]. Finally, two additional approaches for estimating the economic return to DOE's wind energy R&D are described. One is a variant of the core approach. The other uses very different methods, leveraging the extant literature on 2FLCs to assess the impact of R&D investments on wind energy's levelized cost of energy (LCOE) and, therefore, total deployment costs.

2.1. Core approach: public R&D as an accelerant

2.1.1. General approach

The core analysis presented in this paper builds on past work, and it views R&D as an accelerant of technology cost reduction and deployment. NRC [19] first developed and applied this basic framework to assess the historical return on multiple DOE R&D programs. Ruegg et al. [21], and following earlier guidance from Ruegg and Jordan [29], built on this foundation and established more-formalized guidelines for DOE's Office of Energy Efficiency and Renewable Energy when conducting program-level R&D impacts assessments. Finally, Pelsoci [20] used an approach generally consistent with these guidelines to assess the economic return to DOE's past wind energy R&D investments.

The basic framework for retrospective R&D assessments recommended by all of these reports assumes that advancements generated by the public sector would have been accomplished by the private sector alone, but with a delay. This is not to say that every public-sector R&D investment has the same acceleration effect; instead, the implication is that the collective impact of public-sector R&D is to accelerate cost reduction and technology deployment. Pelsoci [20], for example, conducted extensive stakeholder engagement, finding that DOE's wind energy R&D had led to a 6-year acceleration in reducing wind's LCOE and a resulting 6-year acceleration in wind deployment. The NRC [19] study assumed a 5-year acceleration for all DOE programs assessed.

2.1.2. Overview of the Pelsoci study

The Pelsoci [20] report represents the most recent program-level benefit-to-cost analysis of DOE's historical wind R&D investments. The analysis used multiple metrics, including the net present value (NPV) of DOE's investment, benefit-to-cost ratios (BCRs), and internal rate of

¹ Unless otherwise specified, all monetary values are reported in real 2017\$, based on the Gross Domestic Product (GDP) Implicit Price Deflator.

Table 1
Summary of core findings from Pelsoci [20].

	Metrics based on entire DOE wind energy program investment	Metrics based on DOE wind energy investments in selected technologies
Net Present Value at 3%	\$3.5 billion	\$3.8 billion
Net Present Value at 7%	\$0.9 billion	\$1.1 billion
Benefit-to-Cost Ratio at 3%	3.9 to 1	5.3 to 1
Benefit-to-Cost Ratio at 7%	2.1 to 1	2.8 to 1
Internal Rate of Return	12%	14%

return (IRR). The analysis was retrospective, covering 1976 to 2008, and accounted for the “additionality” of the publicly funded R&D by comparing actual market outcomes with what might have happened absent DOE’s investments.

More specifically, Pelsoci [20] relied on subject-matter experts and documentation to judge the combined impacts of a subset of the wind technology advancements supported by DOE. The four categories of technologies considered included wind turbulence models, unsteady aerodynamic experiments, turbine blade material characterization and modeling, and wind turbine component demonstration. Those specific investments over the 1976–2008 period represented 72% of DOE’s overall wind energy R&D budget.

Interviews with experts from research institutes, academia, industry, and project developers suggested that DOE’s R&D investments resulted in the use of more sophisticated industrial design processes that led to higher reliability rates, lower commercial risks, and a lower cost of wind energy. Based on the judgement of the experts, the combined effect of DOE’s investments was to accelerate wind LCOE reduction and wind power deployment by 6 years compared to a counterfactual scenario of no DOE R&D (but with private-sector R&D, and public-sector R&D from other countries). Absent DOE’s investments, Pelsoci concluded that, under the counterfactual “next best alternative technology” scenario, wind turbines would have still been designed (with a 6-year delay) using trial-and-error methods and crude rules of thumb; wind turbine component reliability would have been degraded, resulting in higher outage rates, reduced availability, and higher operation and maintenance expenses; and turbines would have experienced more frequent systemic failures.

The impacts of DOE’s R&D were documented along four dimensions—economic, environmental, energy security, and knowledge—with aspects of the first two estimated in monetary terms. Economic benefits of \$3.3 billion (2008\$) from energy cost savings were estimated by multiplying the LCOE reduction caused by DOE’s investments (via a 6-year acceleration of LCOE trends) in each year by the (lower) wind generation levels that would have occurred absent a 6-year deployment acceleration. Additional benefits of \$9.8 billion came from avoided adverse health incidents due to reduced exposure to particulate matter. These benefits were estimated as the avoided health costs from the displacement of thermal powerplant operations and related air emissions due to the additional wind supply caused by the 6-year deployment acceleration. It was assumed that DOE was responsible for 80% of these cost and health benefits, due to industry cost sharing, resulting in \$10.4 billion in total benefits. After considering total DOE R&D expenditure of \$1.7 billion, net benefits were calculated at \$8.7 billion (2008\$) during 1976–2008. These represent cumulative figures, with no discounting.

Pelsoci [20] then used 3% and 7% real discount rates to estimate the NPV, BCR, and IRR of DOE’s investment, in one case considering the entire DOE wind energy R&D expenditure and in another case considering the 72% of that budget specifically related to the technologies in question (Table 1). Separate from these monetary estimates, Pelsoci [20] also estimated the incremental wind generation due to DOE’s investments, along with the related reductions in carbon dioxide and sulfur dioxide emissions as well as oil demand.

2.1.3. Conducting an updated analysis of DOE’s wind energy R&D²

The analysis in this paper updates and builds on Pelsoci [20], NRC [19], and Ruegg et al. [21]. Where this analysis differs from these past assessments and approaches, clarity is provided on the nature of the differences, and the reasoning for those differences is explained. Most of the differences are methodological improvements on the past work. Table 2 compares the approach and assumptions used in this paper with those from Pelsoci [20], with notable differences detailed below.

Whereas Pelsoci’s analysis considered impacts through 2008, the present analysis extends the assessment to consider wind power deployment through 2017. Moreover, due to data limitations, Pelsoci [20] considered R&D costs back to 1976 but not the benefits associated with some of the very early years of wind deployment in the United States; this analysis resolves those data issues and includes wind deployment from the beginning of the commercial market in 1982 and through 2017 (and R&D investments back to 1976). See Appendix A for the data on U.S. wind capacity additions used in this analysis.

Pelsoci’s analysis presumes that the same absolute LCOE reduction that comes from the 6-year acceleration applies to all wind power production within each given year. This ignores the fact that wind production in any single year comes from wind power plants built in a large number of previous years, and each of those plant vintages will have its own absolute LCOE reduction due to the 6-year acceleration. The present analysis, instead, estimates for each year the amount of wind production that comes from plants built in each of the previous years, and it applies the 6-year LCOE acceleration to each plant vintage separately. This approach requires estimation of vintage-specific wind capacity factors, especially in the early years—specifically, starting point capacity factors,³ and then assumed wind plant degradation after year 10 to year 20 consistent with Wiser and Bolinger [11]. For later years, where possible, the analysis relies on project-specific reported production from the dataset assembled for Wiser and Bolinger [11], while also assuming 2% annual plant-level degradation after year 10. These data had not been assembled when Pelsoci’s study was conducted, but they encompass virtually all wind projects in the United States and so are fully used in the present analysis. The analysis uses data on annual wind power capacity additions from 1982 through 2017 compiled in current and earlier versions of the annual DOE Wind Technologies Market Report (e.g., [11]); see Appendix A.

Pelsoci [20] did not include any consideration of effective useful life (EUL). Specifically, Pelsoci’s analysis extended through 2008, with no benefits considered after 2008 even for wind power plants built in 2008

² All data and calculations, if not otherwise included in this paper or its appendix, are available from the authors upon reasonable request.

³ Early-year average capacity factors are assumed to start at 15% for plants built in 1982 (the first year of commercial wind deployment in the United States), growing to 25%, 30%, and then 33% over time until 1998—at which point actual plant-specific production data from Wiser and Bolinger [11] are used (except for projects built in 2017, which, due to lack of production data, are assumed to have a 45% average capacity factor). Assumed average capacity factors for plants built from 1982 to 1998 derive from an analysis of historical U.S. Energy Information Administration (EIA) wind production and capacity data, as well as early reports from the California Energy Commission summarizing the performance of California wind projects: <https://www.energy.ca.gov/wind/documents/>.

Table 2
Comparison between Pelsoci [20] and the current analysis.

	Pelsoci [20]	Current analysis
R&D performance period	1976 to 2008, but not fully inclusive of early years	1976 to 2017, inclusive of early years
Wind technologies	Focus on four specific areas of DOE investment in land-based wind	Include impact of all DOE wind R&D expenditures on land-based wind
Effective useful life	Not considered	Include EUL in core analysis
Counterfactual	6-year acceleration; 80% attribution to DOE R&D	6-year acceleration; 80% attribution to DOE R&D
Assumed effect	LCOE acceleration & deployment effect	LCOE acceleration & deployment effect
Treatment of increasing LCOE during period in 2000 s	Did not treat this issue	Smooth the resulting LCOE curve
Wind plant vintaging	No	Yes
Real discount rate	7% as primary case, 3% informational	3% as primary case, 7% and undiscounted as informational
Economic benefits included	Energy cost and health benefits	Energy cost and health benefits
Monetized health benefits	EPA COBRA model	Midpoint of multiple advanced models, inclusive of COBRA model
Sensitivity analysis	Attribution range of 72% to 88%	4-year and 8-year acceleration

or before. As a result, the Pelsoci assessment ignored 18 years or so of useful life for wind turbines installed in 2006, given the cutoff of 2008. Ruegg et al. [21] recommended that DOE impact assessments be conducted both ways: not considering EUL and considering EUL. When considering EUL, the analyst does not include wind power plants built after the end year of the assessment (2008 for Pelsoci, 2017 for the current work), but does consider the remaining useful life of wind power plants built up to the end year of the assessment (2017 in this case). The analysis presented in this paper only includes EUL, because the authors consider this to be the only realistic assumption. Here the current analysis differs from Ruegg et al. [21], which recommends that “without EUL” be considered the base case. The Ruegg et al. recommendation seems unduly conservative, because wind power plants are built with project lives of 20 years or more, the industry has experience achieving this target, and the LCOE of wind plants is largely established in the first year and is passed to customers often through long-term power sales agreements. Given this context, it is implausible that R&D benefits that accrue to already-built plants would simply end at the end of 2017, as assumed in a “without EUL” case. The analysis in this paper instead follows NRC [19], which considered EUL in its assessment of DOE R&D programs. In terms of the details, a 20-year project life is assumed for projects installed in 2012 and before, with EUL increasing by 1 additional year each year until a 25-year project life is assumed in 2017. The wind industry has generally moved to 25- or even 30-year project life assumptions in recent years, and DOE’s Wind Energy Technologies Office has assumed a 25-year project life since 2017.

This paper’s core case follows Pelsoci [20] by applying a 6-year acceleration of LCOE and wind deployment due to R&D efforts, and assuming 80% attribution to DOE. By assuming the same 80% attribution factor, this analysis in effect assumes that industry cost sharing has not substantially changed since the Pelsoci assessment, on a percentage basis—discussions with DOE staff suggest that this is a reasonable assumption. The 6-year acceleration assumption not only aligns with Pelsoci, but it is also generally consistent with the 5-year acceleration applied in NRC [19] for DOE’s R&D investments across a broad array of technologies. Nonetheless, this 6-year acceleration assumption may be the most important input to the analysis—and perhaps the one that is most uncertain.

The Pelsoci [20] counterfactual was derived through careful expert elicitation designed specifically for the period up to 2008—it was not intended to be used for the post-2008 period of R&D performance. A decade has passed since Pelsoci’s analysis, and the current analysis does not draw from new comprehensive industry interviews or new analysis to validate the 6-year acceleration assumption for more-recent years. Thus, there is uncertainty about whether this 6-year acceleration is accurate, especially with extension of the analysis through 2017. As the industry has matured over the last decade, the relative contribution of DOE’s R&D to overall industry-wide cost reduction and deployment

acceleration might have declined. At the same time, DOE’s wind R&D goes well beyond the four technology areas evaluated in Pelsoci [20], which would be expected to enhance the overall acceleration effect of DOE funding. External reviewers of this paper offered a range of divergent opinions on the 6-year acceleration assumption.⁴

Given the uncertainties, a sensitivity analysis is conducted to test the impacts of varying the acceleration assumption, including 4- and 8-year accelerations. Moreover, all three levels of acceleration are applied over the entire analysis period, not only over the timeframe since the Pelsoci [20] assessment. This reflects underlying uncertainties not only about the degree of acceleration after 2008, but also uncertainties prior to 2008. Future expert elicitations could help refine these estimates and potentially document how the degree of acceleration has changed over the 40-year duration of DOE’s wind energy investments as the sector has evolved and as other countries have invested in public-sector wind R&D.

As summarized previously, Pelsoci’s assessment and the Ruegg et al. [21] guidance consider acceleration of both LCOE and deployment. LCOE-related economic benefits were estimated by multiplying the LCOE reduction caused by DOE’s investments (via the 6-year acceleration of LCOE trends) in each year by the (lower) wind generation levels that would have occurred absent a 6-year deployment acceleration. Environmental benefits from avoided adverse health incidents were estimated by assessing the health benefits of the additional wind energy due to the 6-year deployment acceleration and the resulting reduction in criteria air pollutants, compared with the counterfactual case. The analysis conducted in this paper applies this same basic approach for both LCOE and deployment acceleration.

When considering health benefits, Pelsoci [20] focused on the monetary benefits of reduced health incidences from particulate matter exposure, using the U.S. Environmental Protection Agency’s (EPA’s) Co-

⁴ External reviewers highlighted a range of opinions about the 6-year acceleration assumption. Some reviewers noted the intangible and hard-to-quantify impacts from DOE’s R&D, specifically mentioning early work to understand the grid-integration issues associated with wind energy, efforts to establish a future vision in which wind energy is a meaningful contributor to U.S. electricity supply, and support for training the next generation of technical and industry leaders. Other reviewers identified examples in which the impact of DOE’s R&D was likely well in excess of a 6-year acceleration of what might have been accomplished without DOE investments, either in enabling cost reduction or in supporting additional wind deployment. On the other hand, another reviewer noted that, given public R&D investments in Europe especially, the accelerant effect of DOE’s unique investments might be somewhat lower, specifically mentioning 4 years as potentially a best guess. Another reviewer noted that the degree of acceleration may have shifted over time. These varied and divergent opinions reflect the uncertainty about the degree of acceleration, and they justify the approach of assessing assumptions ranging from 4 to 8 years as well as the later suggestion that new research be conducted to refine and update the acceleration figures.

Benefits Risk Assessment (COBRA) model. Ruegg et al. [21] also recommended the use of COBRA. The present analysis includes both a broader set of pollutants and a larger number of (sometimes more advanced) models, including but not restricted to COBRA—following the “midpoint” results from Millstein et al. [30]. Millstein et al. [30] is the most advanced effort to date for estimating the health and environmental benefits of historical wind (and solar) deployment, but it focuses on the years 2007 to 2015. The current paper extends the analysis to consider years prior to 2007 and after 2015. This analysis does not use the Millstein et al. [30] results directly, because that study estimates the impacts of all U.S. wind deployment; instead, intermediate results are used to extrapolate findings to the wind deployment acceleration cases.⁵

Ruegg et al. [21] also recommended using the social cost of carbon to estimate monetary benefits from carbon reductions, albeit suggesting that the results be presented separately. Given current uncertainties about the proper social cost of carbon to apply within U.S. federal decision making, this analysis instead follows Pelsoci [20] and reports carbon emissions reductions in physical units. As with health impacts, Millstein et al. [30] is used and extended in time to assess the carbon emissions reductions caused by the R&D-induced wind deployment acceleration.

Estimating an LCOE-acceleration effect requires data on the historical LCOE of wind energy. Historical LCOE data come from DOE [31] and Wiser and Bolinger [11]. Unlike in Pelsoci [20], these LCOE data are “smoothed” via interpolation. The LCOE of U.S. wind increased for a period in the 2000s owing to a variety of unique factors, including currency exchange rate movements, higher materials input prices and labor costs, and a supply-demand balance that favored suppliers over purchasers [32]. Application of a 6-year acceleration assumption during this period without smoothing leads to the unlikely result that DOE R&D caused LCOE increases in some years; it seems implausible that DOE R&D investments helped cause unfavorable currency movements, heightened materials and labor prices, or global supply-demand imbalances. The development of an interpolated, smoothed LCOE curve that adjusts LCOE downward during this period resolves this issue. The resulting historical LCOE data for land-based wind are shown in Appendix A. In addition, the estimated reduction in LCOE due to DOE’s R&D in the 4-, 6-, and 8-year acceleration cases is shown later, in Fig. 7, for reference.

The DOE direct wind R&D budgets from 1976 through 2017 were provided by DOE’s Wind Energy Technologies Office (see Appendix A). Based on available data from 2014 through 2017, 8% is added to these figures in each year to account for DOE staff and management costs.

The results of the analysis are reported based on cumulative, undiscounted figures (in 2017\$) and based on 3% and 7% real discount rates (discounting costs and benefits to 1976, in 2017\$). NRC [19] reported DOE R&D outcome results using a 0% discount rate, in part due to the problems of comparing R&D impacts over widely disparate periods. The Office of Management and Budget has recommended the use of both 7% and 3% to reflect private and social rates of discount [33–34]. Ruegg et al. [21] recommend the use of a 7% real discount rate as the primary case, with 3% as informational. Ultimately, this paper emphasizes the 3% case, but analysis results also include the 7% and undiscounted cases. DOE’s investments in wind R&D span four decades, and interest rates are at present very low by historical

standards. Use of a real 7% discount rate results in severe front-loading, effectively ignoring recent impacts. Using a 3% real discount rate appears more appropriate when considering the social impacts of long-term DOE R&D investment, especially in a relatively low interest rate environment.

Analytically, the approach (with some abstraction, especially vis-à-vis the complexities of plant vintaging) can be summarized by the following equations.

Present value total benefits (PVTB)

$$= PV \text{ cost benefits (PVCB)} + PV \text{ health benefits (PVHB)}$$

where

$$PVCB = A * \sum_{t=1}^t \frac{(LCOE_{t-a} - LCOE_t) Q_{t-a}}{(1+r)^t}$$

$$PVHB = A * \sum_{t=1}^t \frac{(Q_t - Q_{t-a}) MHB_t}{(1+r)^t}$$

Meanwhile:

$$\text{Present value R\&D costs (PVRDC)} = \sum_{t=1}^t \frac{\text{Annual R\&D cost}_t}{(1+r)^t}$$

And finally:

$$\text{Benefit cost ratio (BCR)} = PVTB/PVRDC$$

where

LCOE = levelized cost of energy (albeit, in this simplified equation, ignoring vintaging complexities)

MHB = marginal health benefits of 1 MWh of wind

Q = quantity of wind energy

A = attribution percentage

t = time

a = rate of acceleration

r = discount rate

The resulting analysis findings may be conservative—understating the impacts of DOE’s R&D investments. First, the analysis considers the cost of DOE’s wind energy R&D to equate to its total investments in wind, inclusive of all areas of R&D focus. While this is consistent with the core results presented in Pelsoci [20], Pelsoci also notes that the specific investments that relate to the 6-year acceleration assumption represent 72% of historical DOE wind expenditures. More broadly, DOE’s wind R&D has focused on not only land-based wind, but also on offshore and distributed wind. All such R&D costs are included in the present analysis, but benefits solely include those that derive from utility-scale land-based wind. Second, the analysis does not consider any R&D benefits associated with wind power plants built in 2018 or after. This assumption is consistent with the guidance in Ruegg et al. [21], but is highly conservative in that it assumes that R&D benefits do not “spill over” into future years. NRC [19], in contrast, generally assumed that R&D benefits would persist for an additional 5 years of technology deployment. Third, while carbon emissions reductions are reported in physical terms, the present study does not translate those reductions into monetary benefit estimates. A large and varied literature has developed to estimate the global and domestic benefits of carbon reductions, which could in the future be used to extend this assessment. Fourth, and more generally, while the full DOE wind R&D budget is included, the current study does not assess or monetize a number of additional possible benefits that may have emerged from those expenditures. For example, it does not consider water use, cross-industry knowledge spillover, or any other possible benefits.

The primary factor that may push in the other direction (toward overstating the impacts of DOE’s R&D investments) is the acceleration

⁵ An advantage of Millstein et al. [30] is that it used advanced methods to establish regional estimates of the marginal emissions reductions and health benefits of wind energy. To extrapolate those 2007–2015 findings to years prior to 2007, the current analysis accounts for changes to the regional distribution of wind power and regional changes to power-sector emissions, as well as population and GDP. To extrapolate the findings beyond 2015, the analysis considers population and GDP growth as well as EIA estimates of power-sector emissions. The methods and resulting data are available upon reasonable request.

assumption. The 6-year assumed acceleration—and the range of 4–8 years—may be too aggressive. At a minimum, it is a core source of uncertainty in this assessment.

2.2. Alternative approaches to estimating R&D impacts

As points of comparison, two alternative approaches are used to estimate the economic return on DOE's wind energy R&D investments. Both of these approaches focus exclusively on the LCOE acceleration effect, with no induced wind deployment impacts. First, the analysis loosely applies the methods established in NRC [19], Ruegg and Jordan [29], Pelsoi [20], and Ruegg et al. [21], but assumes only an LCOE-reduction acceleration effect with no wind deployment acceleration. Second, the analysis leverages the academic literature on 2FLCs, and it develops three distinct estimates of the economic return on DOE's wind energy R&D. These three estimates also focus only on the LCOE effect. These approaches are not perfectly comparable to the core methods, described previously, because they capture different impact pathways. Nonetheless, contrasting the results from different methods can help assess, in broad terms, the reasonableness of the core results.

2.2.1. LCOE-only acceleration

The core methods described previously assume both LCOE and deployment acceleration, consistent with previous research. However, alternative scenarios are assessed in which there is only an LCOE effect. These scenarios consider only economic benefits, presuming that the lower LCOE due to DOE R&D reduces the cost of all realized historical wind deployment. There are no incremental health or environmental benefits associated specifically with DOE R&D, because it is assumed that those R&D investments reduced the cost of wind power deployed but not the volume of that deployment. These “LCOE only” scenarios therefore result in higher LCOE-based economic benefits but no assumed R&D-induced health and environmental impacts.

The assumptions that underlie this approach might be justified if, for example, wind deployment is primarily the result of policy drivers that would have existed even absent DOE R&D investment—state renewables portfolio standards, for example, or federal tax incentives. This is an extreme assumption, because both policy and economic drivers have surely been important in motivating wind deployment. Nonetheless, policy has played a major role, so this approach can be viewed as a potentially useful bounding case that need not rely on uncertain estimates of potential health benefits. One other benefit of these “LCOE only” scenarios is that they can be more readily compared to the 2FLC results, which similarly only consider LCOE-related benefits.

2.2.2. Two-factor learning curves

Learning curves have been used extensively to better understand historical cost reductions for a variety of energy-generation technologies, and in other cases to forecast future costs. In the simplest application, single-factor learning curves define a relationship by which cumulative increases in experience lead to progressively lower costs. As applied to wind energy or other generation sources, the most common proxy for “experience” is cumulative installed capacity. With a log-log formulation being typical, every doubling of cumulative wind power capacity can be assumed to lead to a specific percentage reduction in the cost of wind—the learning rate.

Learning curves have a long history within the wind power sector (e.g., [14,27,28,35]), with recent analyses suggesting slightly below 10% to nearly 20% LCOE reductions for land-based wind for every doubling of cumulative global capacity [36,37,12,38]. Nonetheless, learning curves have been criticized. One pertinent criticism is that single-factor learning curves simplify the many causal mechanisms that lead to cost reduction, effectively assuming that cumulative installed capacity is the dominant driver for all cost improvements [39,40,35].

Two-factor learning curves are meant to provide incremental

insight, by explaining historical cost reductions based on two possible drivers rather than one. Specifically, like a single-factor learning curve, the 2FLC also includes an experience variable, often using a proxy like cumulative installed capacity and leading to a learning-by-doing (LBD) rate. Unlike the single-factor formulation, however, the 2FLC also includes a variable for “knowledge stock,” often using as proxies cumulative R&D investments and/or patent activity and leading to a learning-by-researching (LBR) rate. Because new knowledge takes time to diffuse into commercial products and may also become stale over time, knowledge stock variables often include assumptions for knowledge lag and depreciation.

The basic formulation of a 2FLC in this case is as follows:

$LCOE_Q = LCOE_1 Q^{b_K} K^c$, or expressed in logarithmic form as follows:

$$\log LCOE_Q = \log LCOE_1 + b \log Q + c \log K$$

$$LR_{LBD} = 1 - 2^b$$

$$LR_{LBR} = 1 - 2^c$$

where

$LCOE_Q$ = levelized cost of wind energy at cumulative installed capacity Q

$LCOE_1$ = levelized cost of wind energy for the first unit ($Q = 1$)

b = experience parameter associated with cumulative installed capacity (Q)

c = experience parameter associated with cumulative knowledge stock (K)

LR_{LBD} = learning-by-doing learning rate

LR_{LBR} = learning-by-researching learning rate

A number of researchers have constructed and/or discussed 2FLCs for wind energy, including Wiesenthal et al. [41], Wiesenthal et al. [42], Yu et al. [43], Wiebe and Lutz [44], Miketa and Schrattenholzer [45], Kobos et al. [46], Jamasb [47], Söderholm and Sundqvist [48], Söderholm and Klaassen [49], Ek and Söderholm [39], Klaassen et al. [50], Goff [51], Grafström and Lindman [52], Cory et al. [53], Lindman and Söderholm [27], Rubin et al. [28], and Kahouli-Brahmi [54]. These authors have used a variety of specifications and data sources, making comparisons difficult. More generally, there are various challenges to constructing 2FLCs. For example, much of the work conducted to date has focused on explaining the upfront installed cost of wind energy, not the more relevant metric of all-in levelized costs, considering performance changes, operations and maintenance cost reductions, and other factors beyond installed costs. Moreover, interactions are expected between experience and knowledge stock, yet interaction terms have rarely been employed. Incomplete data on wind energy R&D expenditures—whether globally or regionally—often must be used, and knowledge spillovers across countries, firms, and even different industrial sectors are not always well thought out or considered. Finally, in part due to inadequate data on private R&D, most analysts have focused on the impact of public R&D; more generally, knowledge stock may be influenced by various factors beyond R&D expenditures that are otherwise not included in the analysis.

Despite the limitations of this past work, this paper builds on it to assess the impact of public wind R&D on the cost of wind energy through 2FLCs, focusing ultimately on the impact of DOE's wind R&D investments. In this case, only an LCOE-related effect is included, with no deployment-oriented impact. The application of 2FLCs in this way is novel. The authors are unaware of any previous research that has extended the application of these tools not only to assess the impacts of R&D on technology costs, but also to develop R&D net-return performance measures.

Specifically, this paper estimates the impact of historical global public R&D knowledge stock on the LCOE of wind energy. The base assumption is that global public wind R&D knowledge stock is

equivalent to cumulative global public R&D expenditure on wind reported by IEA [18],⁶ with a 2-year lag and 3%/year depreciation (Fig. 1); this assumption is generally consistent with past work. The analysis then assumes that the per-dollar impact of U.S. public R&D knowledge stock has been equivalent to the per-dollar impact of other global R&D knowledge stock in contributing to global knowledge stock—in effect assuming equivalent marginal impacts from U.S. or other country investments on the LCOE of wind in the United States. This may be a conservative assumption, because one might alternatively presume that DOE R&D investments have, in part, been targeted towards issues that are unique to the domestic market and so have had a larger marginal impact on U.S. wind LCOE than the R&D investments made by other countries. Regardless, the resulting impact of DOE R&D on land-based wind LCOE over time is then multiplied by U.S. wind electricity supply to estimate an economic benefit of DOE's R&D expenditure. No deployment effect or health benefits are included; instead, the analysis assumes that the LCOE-related effect applies to the full amount of historical wind energy supply.

To further bolster confidence in these estimates, three distinct 2FLC approaches are employed to estimate the likely impact of historical DOE R&D investments on wind LCOE and therefore overall economic impacts:

- **Literature Review—Shift:** This approach leverages the meta-analysis in Lindman and Söderholm [27]. That study, based on an analysis of the 2FLC literature at the time, found that inclusion of knowledge stock in a learning specification resulted in a change to the single-factor learning-by-doing rate of 2.165 percentage points. A single-factor learning curve is first established, based on U.S. wind LCOE and cumulative historical global wind capacity, leading to a learning-by-doing rate of 16%. The analysis then uses the Lindman and Söderholm [27] finding that, without global R&D, the single-factor learning rate would be 2.165 percentage points lower, to derive an estimated historical wind LCOE had there been no global wind R&D investments.⁷ The resulting gap between the “with R&D” and “without R&D” LCOE estimates over the 1982–2017 period represents the impact of global wind R&D on historical U.S. wind LCOE by plant vintage. Finally, the contribution of DOE's wind R&D to this total LCOE impact is estimated by multiplying the annual LCOE gap by the annual estimated contribution of DOE R&D to global wind knowledge stock (equivalent to the portion of global knowledge stock derived from DOE wind R&D investments). The analysis further assumes that the IEA [18] database of global public R&D investments is incomplete, so it reduces the estimated U.S. contribution to total global knowledge stock in each year by (an admittedly somewhat arbitrary) 5%. Based on the method described, the U.S. contribution to global knowledge stock, and therefore to the total LCOE reduction from global wind R&D, is estimated to start at 64% in 1980 and decline to 23% by 2017.
- **Literature review—LBR:** This approach builds on the literature review summarized in Rubin et al. [28]. That study finds a median LBR rate of 16.5% in the available literature, meaning that a doubling of cumulative knowledge stock leads to a 16.5% reduction in upfront wind energy costs. The present analysis assumes that this median literature-based LBR rate applies to global public R&D knowledge stock—again using R&D expenditure data from IEA

[18]—and U.S. wind LCOE.⁸ With these assumptions, a full 2FLC is developed that is consistent with the U.S. land-based wind LCOE estimates, which is then used to estimate U.S. wind LCOE under two scenarios: with all global R&D and with all global R&D except DOE R&D. The resulting gap between the “with global R&D” and “without DOE R&D” LCOE estimates over the 1982–2017 period represents the estimated impact of DOE's wind R&D investments on historical U.S. land-based wind LCOE by plant vintage.

- **Own Estimates—LBR:** Finally, data on U.S. land-based wind LCOE, global cumulative wind capacity, and global R&D knowledge stock are used to estimate a new 2FLC unique to the present analysis. This simple regression yields a LBR rate of 33%, meaning that a doubling of cumulative global knowledge stock leads to a 33% reduction in LCOE. Using these 2FLC regression results, U.S. wind LCOE is estimated under two scenarios: with all global R&D and with all global R&D except DOE R&D. The resulting gap between the “with global R&D” and “without DOE R&D” LCOE estimates over the 1982–2017 period represents the estimated impact of DOE's wind R&D investments on historical U.S. land-based wind LCOE by plant vintage. Although the estimated LBR rate of 33% is barely statistically significant (p-value is ~ 0.075), alternative knowledge lag and depreciation assumptions yield a wide range of estimated LBR rates, with results that are often not statistically significant. Results are clearly very sensitive to assumptions about knowledge lag and depreciation, and they are not sufficiently precise to pinpoint a firm LBR rate. In addition, the estimated 33% LBR rate is on the high end of rates in the available literature, though it is consistent with a similar U.S.-focused analysis in Cory et al. [53]. One possible reason for the higher LBR rate found in the present work as well as in Cory et al. [53] is that both focus on wind LCOE, whereas the remainder of the literature emphasizes solely project- or turbine-level upfront installed costs.

The resulting estimated annual LCOE impacts from DOE's R&D investments for wind power projects built from 1982 to 2017 are summarized later, in Fig. 7, and are multiplied by appropriately vintaged wind production data each year (using the same methods described previously) to estimate monetary savings. The previously described approaches to EUL and discounting are applied here as well.⁹

3. Results

To narrow the number of results presented and to enable comparisons across scenarios and sensitivities, this paper focuses on BCRs. Results are also presented in absolute dollar terms in some cases. Additional results and metrics can be found in Appendix B.

3.1. Core results: 6-year acceleration of LCOE and deployment

The core analysis follows Pelsoci [20] by assuming 6-year acceleration of LCOE and wind deployment due to DOE R&D efforts, with 80% attribution to DOE. Using the assumptions and methods described in Section 2, Table 3 summarizes the core economic return and impact measures for the assessment.

Focusing on the 3% real discount rate case to calculate present-value estimates, DOE's wind R&D investments totaled \$1.7 billion.

⁶ However, the IEA [18] data for DOE wind R&D are replaced with DOE's own estimates of its expenditures; in this case, the analysis does not include DOE staff and management costs.

⁷ The literature assessed by Lindman and Söderholm [27] applied 2FLCs to wind plant or turbine installed cost, whereas this paper applies the resulting 2.165 percentage point result to an LCOE-based learning specification. This paper's application is likely conservative, because wind LCOE has declined to a greater extent than upfront installed costs have—and wind R&D has focused on both cost reductions and performance improvements.

⁸ The literature on which the 16.5% is based focused principally on wind plant installed costs, and it used a wide variety of specifications to define knowledge stock. The application in this paper is likely conservative, because wind LCOE has declined to a greater extent than upfront installed costs have—and wind R&D has focused on both cost reductions and performance improvements.

⁹ The detailed analyses, data, and results for these three approaches are available upon request.

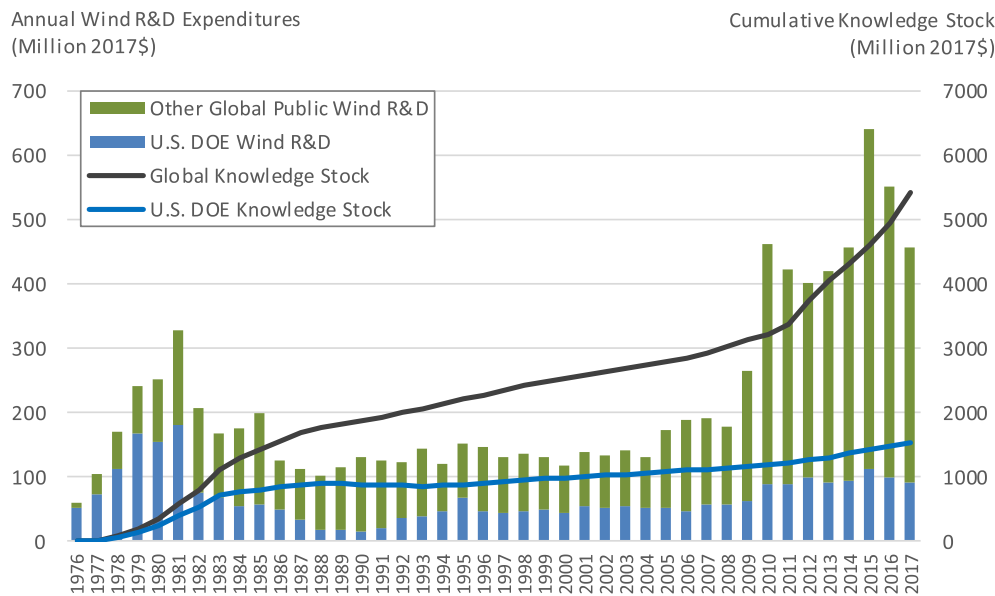


Fig. 1. Global Wind R&D Expenditures and Knowledge Stock. Notes: Global (and DOE) knowledge stock is equivalent to cumulative global public (and DOE) R&D expenditure on wind, with a 2-year lag and 3%/year depreciation.

Table 3

DOE wind energy R&D impact summary: 6-year acceleration in LCOE and deployment (1976–2017, with EUL to 2042).

Metric	Not Discounted	3% Discount Rate **	7% Discount Rate **
DOE portfolio investment cost (1976–2017, billion 2017\$)	\$3.0	\$1.7	\$1.1
Monetary value of energy cost benefits (billion 2017\$)	\$27.1	\$8.3	\$2.2
Monetary value of avoided adverse health incidences (billion 2017\$)	\$89.5	\$24.9	\$5.3
Total combined economic benefit (billion 2017\$)	\$116.6	\$33.1	\$7.5
Present Value of Net Benefits (billion 2017\$)	\$113.6	\$31.4	\$6.4
Benefit-to-Cost Ratio	38 to 1	18 to 1	6 to 1
Internal Rate of Return (IRR)	15.4%	15.4%	15.4%
Increased wind energy generation (1976–2042, GWh)*	←3,180,000→		
Percentage decrease in wind generation without R&D investment*	←57%→		
Avoided carbon dioxide due to DOE R&D (million metric tons CO ₂)	←1,510→		

* Not adjusted downward to account for 80% attribution assumption.

** Discounted to 1976, in 2017\$, based on 3% and 7% real discount rates. Nominal \$ are converted to real \$ based on the GDP Implicit Price Deflator. The non-discounted results are also presented in real 2017\$.

Those investments are estimated to have yielded \$8.3 billion in energy cost benefits due to reduced land-based wind LCOE, and an additional \$24.9 billion in health benefits. The total present value of net benefits is \$31.4 billion, with a BCR of 18 to 1 (i.e., 31.4/1.7). Given the 6-year deployment acceleration, total cumulative wind energy supply is substantially higher than what would have been achieved absent DOE investment, also resulting in avoided carbon dioxide emissions of 1510 million metric tons (monetization of the carbon-reduction benefits would yield a higher BCR). When applying a 7% real discount rate, net benefits drop to \$6.4 billion, with a BCR of 6 to 1. The undiscounted column in Table 3 shows higher total net benefits or \$113.6 billion and consequently a higher BCR of 38 to 1.

Fig. 2 illustrates the time profile of the R&D investments, the energy cost benefits, and the health benefits; the resulting IRR is 15.4%. The deployment-oriented health benefits exceed the energy cost benefits.¹⁰

3.2. Varying rates of LCOE and deployment acceleration

Given uncertainty in the 6-year acceleration input, a sensitivity analysis was conducted by applying 4- and 8-year accelerations as alternative assumptions. Fig. 3 presents the BCRs for the 4-year, 6-year,

and 8-year acceleration cases, considering both energy cost and health impacts.

Focusing on the 3% discount rate case, the 18 to 1 BCR for the base 6-year acceleration scenario increases to 21 to 1 when assuming 8-year acceleration, and it drops to 14 to 1 in the 4-year acceleration case. Naturally, these BCRs decline when a 7% discount rate is used, and they increase when undiscounted figures are presented. Not shown in the figure or monetized in this analysis are carbon dioxide emission reduction benefits, which increase from 1510 million metric tons in the 6-year acceleration case to 1790 million metric tons under 8-year acceleration, and drop to 1120 million metric tons when assuming 4-year acceleration.

Overall, these core results fall within a relatively narrow BCR band of 14-to-1 to 21-to-1, when a 3% discount rate is used. As shown in the figure, the sensitivity of BCRs to discount rates is higher than the sensitivity of BCRs to the rate of LCOE and deployment acceleration. Importantly, across all acceleration and discount rate sensitivities, the economic return to DOE's wind R&D is found to have been positive—the lowest BCR shown in Fig. 3 is 5-to-1, indicating benefits that are 5 times larger than costs.

¹⁰ Full details on the results of all the analyses are available on request.

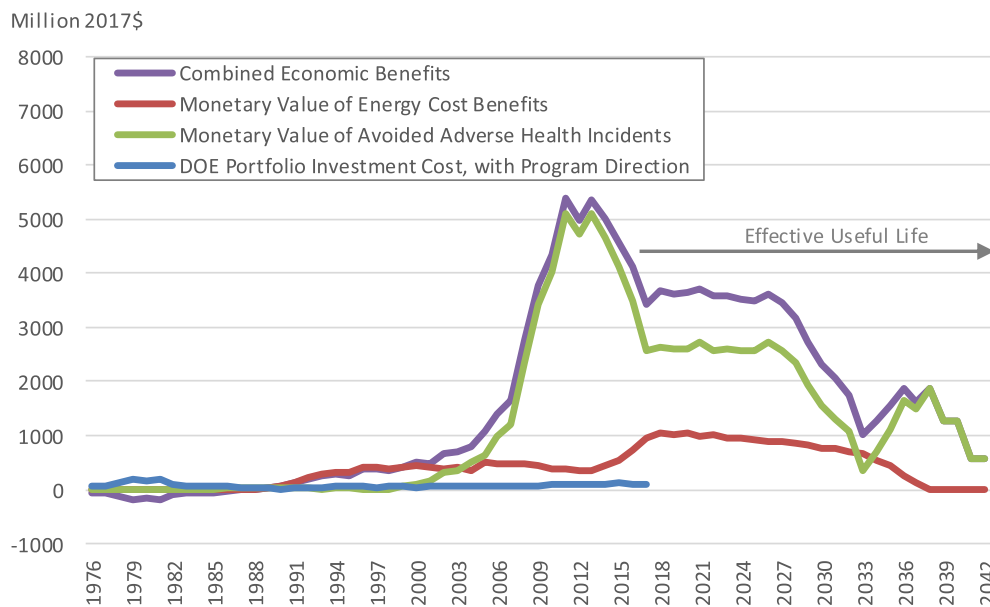


Fig. 2. Time Profile for DOE Wind R&D Investments and Impacts: 6-year Acceleration in LCOE and Deployment.

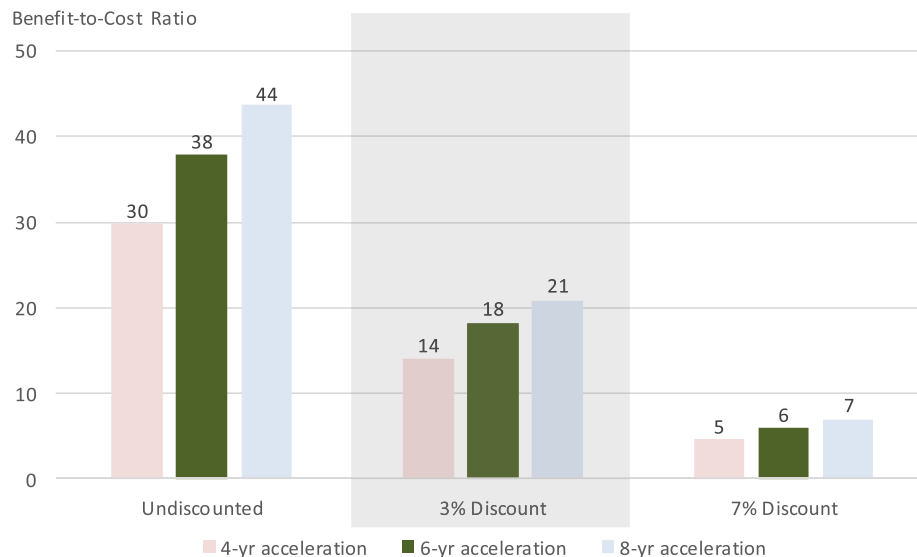


Fig. 3. Benefit-to-Cost Ratios for Various LCOE and Deployment Acceleration Assumptions.

3.3. Comparison to Pelsoci results

As a point of comparison, Pelsoci [20] estimated an overall BCR (considering energy cost savings and health benefits) of 3.9 to 1 at a 3% discount rate. However, the Pelsoci analysis only covered the period 1976–2008, and it did not account for EUL. If the present analysis similarly focuses only on the 1976–2008 period and does not include EUL, the BCR is 3.2 to 1 at a 3% discount rate. If the period of analysis is updated to 1976–2017 but EUL is excluded, the BCR increases to 10 to 1. Finally, reflecting the core results presented above, if the full period and EUL are considered, the BCR is 18 to 1. As such, extending the timeframe of the analysis and including EUL are both key drivers for the higher BCRs found in the present analysis when compared to Pelsoci [20].

3.4. Alternative approach: LCOE-Only acceleration

As described in Section 2, the alternative LCOE-only acceleration results only consider energy cost benefits, but they presume that the

lower LCOE due to DOE R&D reduces the cost of *all* realized historical wind deployment; there are no incremental health benefits, because it is assumed that R&D investments did not affect the amount of wind deployment and therefore did not directly offset generation from thermal power plants. As a consequence, the LCOE-only scenarios result in higher LCOE-based energy cost benefits but no assumed health and environmental impacts.

Fig. 4 presents the resulting BCRs under 4-, 6-, and 8-year acceleration scenarios. Applying a 3% discount rate, the BCR is 12 to 1 when a 6-year acceleration is used, ranging between 8 to 1 and 18 to 1 when alternative 4- and 8-year acceleration assumptions are employed. The BCRs decline when a 7% discount rate is used, and they increase when no discounting is applied. Overall, these BCRs are in the same general range as—albeit somewhat lower than—the core results that consider LCOE and deployment acceleration.

3.5. Alternative approach: two-factor learning curves

Here the core results are compared to the three distinct applications

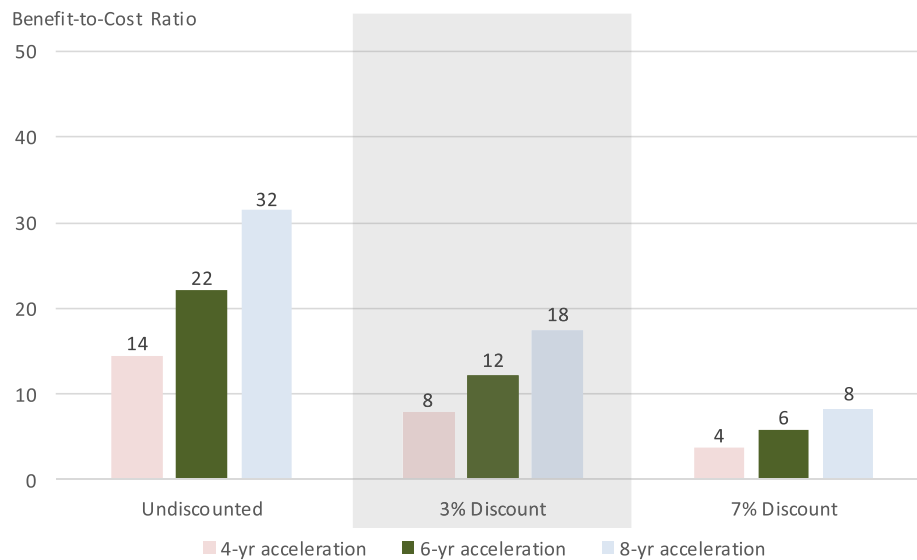


Fig. 4. Benefit-to-Cost Ratios for Various LCOE-Only Acceleration Assumptions.

of 2FLCs: literature review—shift, literature review—LBR, and own estimates—LBR. As described in Section 2, only an LCOE-related effect is included in these cases, with no deployment-oriented impact.

Fig. 5 presents the results of the three 2FLC analyses, focusing exclusively on BCRs. The two literature-review based estimates are consistent with each other, showing BCRs in a similar range: 9 to 1 (shift) and 7 to 1 (LBR), when employing a 3% real discount rate. An updated estimate of a 2FLC leads to a notably higher BCR of 17 to 1 (3% discount rate), but, as indicated previously, the regression results that underlie this estimate are not especially stable.

The overall range of 2FLC results is broadly consistent with the LCOE-only acceleration results presented above.

3.6. Comparisons across all results

Fig. 6 illustrates the general consistency among the results of the alternative approaches and the core results. These various estimates are not perfectly comparable, because they capture different impact pathways. However, the consistency of the results when using very different methods reinforces, in broad terms, the reasonableness of both sets of alternative estimates as well as the core results that consider both LCOE

and deployment acceleration. That the core “LCOE and deployment acceleration” results show somewhat higher economic return measures in general is, in part, due to the fact that the estimated health benefits of wind deployment acceleration are higher than the estimated cost-reduction benefits of LCOE acceleration, on a per-unit of wind basis.

Finally, each of the approaches used to assess the economic impact of DOE’s wind R&D investments results in an estimated LCOE effect—namely, the downward pressure exerted on land-based wind LCOE due to the investments in public wind R&D. As such, one final way to illustrate the full set of results is to depict the estimated LCOE impact of DOE’s wind R&D over time.

Fig. 7 presents these LCOE-reduction estimates, for the 6-year, 4-year, and 8-year acceleration cases, as well as for each of the 2FLC-based analyses. Each line represents the estimated contribution to land-based wind LCOE reduction over time of DOE’s wind R&D investments.

As shown, there are considerable differences in the estimated impact of DOE’s wind energy R&D on LCOE, especially in the 1980s and 1990s. The imprecision in the early-year estimates does not, however, have a dramatic impact on the resulting BCRs—especially in the case of a 3% discount rate—because relatively little wind energy deployment occurred in these early years. In more recent years, there is more

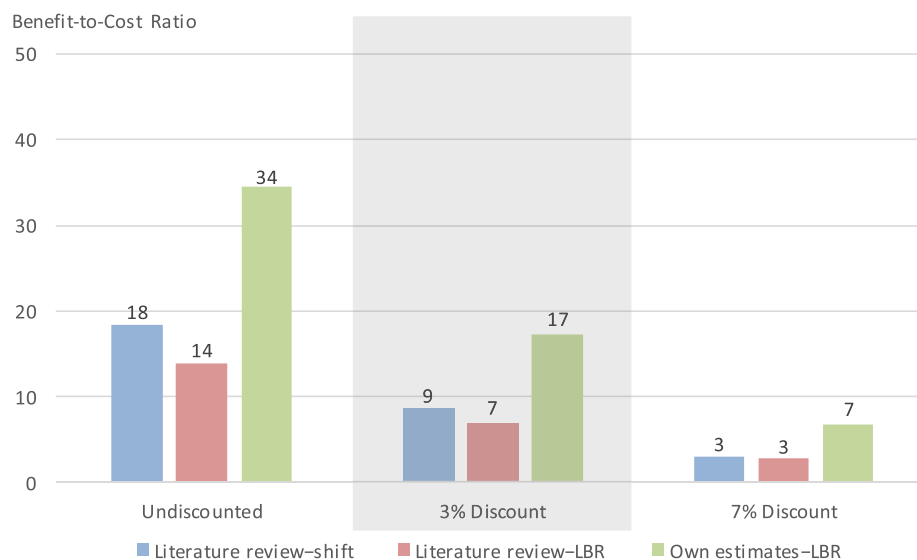


Fig. 5. Benefit-to-Cost Ratios for Two-Factor Learning Curve Assessment.

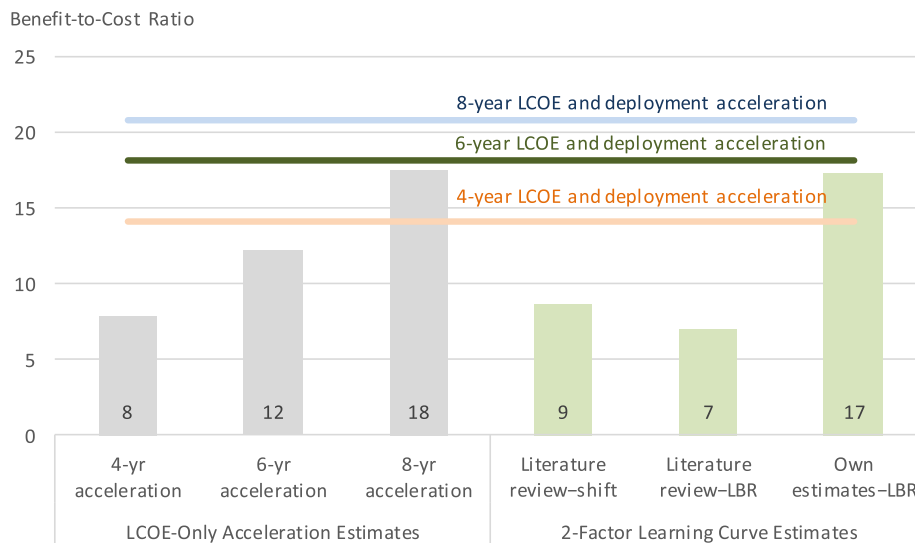


Fig. 6. Comparison of Core Results to Alternative Approaches: 3% Discount Rate.

agreement among the estimated LCOE impacts of DOE's R&D investments, ranging from \$4/MWh to \$9/MWh for wind projects built in 2017 based on the 2FLC-based approaches, and equaling \$12/MWh in the 6-year acceleration case (ranging from \$9/MWh to \$14/MWh when considering the 4-year and 8-year acceleration cases, respectively).

4. Summary of findings

This study assesses the economic return on the U.S. Department of Energy's historical wind energy R&D investments, testing the sensitivity of these findings to various assumptions and approaches. The analysis builds on the basic framework developed and applied in earlier work to conduct retrospective assessments of U.S. energy-related research investments, and it employs two-factor learning curves to provide another means of estimating impacts.

The analysis demonstrates sizable, positive economic returns on the U.S. federal government's wind energy R&D. The core analysis assumes a 6-year acceleration of wind cost reductions and deployment, leading to an estimated benefit-to-cost ratio of 18 to 1 when a 3% real discount rate is used and both energy cost and health benefits are considered. Avoided carbon dioxide emissions are not valued in monetary terms, but they are estimated at 1510 million metric tons. For reasons

discussed previously, the results may be conservative—understating the impacts of these R&D investments.

In recognition of the uncertainty in the degree of acceleration, alternative cases of 4-year and 8-year acceleration are explored. Focusing on the 3% discount rate case, the 18 to 1 benefit-to-cost ratio for the base 6-year acceleration scenario increases to 21 to 1 if 8-year acceleration is assumed, and it drops to 14 to 1 in the 4-year acceleration case. Carbon dioxide emission reduction benefits increase to 1790 million metric tons under 8-year acceleration, and they drop to 1120 million metric tons when assuming 4-year acceleration. Overall, these results fall within a relatively narrow band of benefit-to-cost ratios, ranging between 14 to 1 and 21 to 1, when a 3% discount rate is used. The sensitivity of the results to discount rates is also tested, with higher discount rates leading to lower benefit-to-cost ratios, and lower discount rates yielding higher benefit-to-cost ratios.

To enhance confidence in the core findings, two alternative approaches to estimating the economic return on wind energy R&D investments are applied, both of which focus exclusively on the cost-acceleration affect with no assumed deployment impact. The resulting benefit-to-cost ratios from the alternative approaches range between 7 to 1 and 18 to 1 when a 3% discount rate is used—within the same basic range as the core results. These various estimates are not perfectly

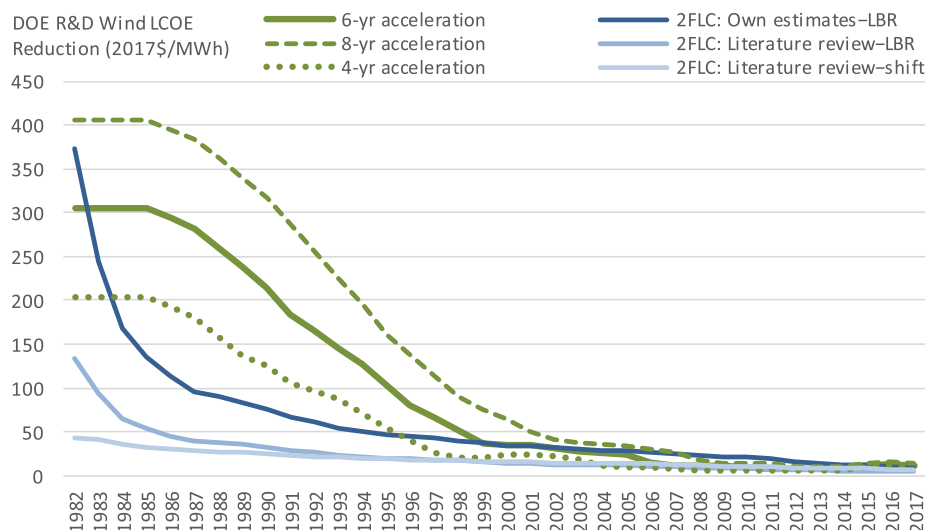


Fig. 7. Land-based Wind LCOE Reduction Due to DOE Wind R&D Investments.

comparable, because they capture different impact pathways. However, the consistency of these results when using very different methods reinforces, in broad terms, the reasonableness of the basic findings of this analysis.

5. Recommendations

These results suggest that continued—and even expanded—publicly funded wind energy R&D may be warranted. The economic returns to past investments have been sizable, and those results are robust across varying input assumptions and analytical approaches. In addition, despite the growing maturity of the wind power industry, substantial opportunities remain for continued advancements and cost reductions, both for land-based wind and offshore wind (e.g., [55,13,36]).

That said, this is not the final word on the subject. Past results do not guarantee future performance. Moreover, additional independent analysis and validation could help refine the estimates presented in this paper, whereas other methods might be used to deepen understanding of what kinds of wind energy R&D investments are most likely to have maximum positive impact.

In relation to improving the economic return measures presented in this paper, several opportunities deserve special mention. First, one of the most uncertain parameters is the degree of acceleration in land-based wind cost reductions and deployment, which may have changed over time as the industry has matured and the role of the U.S. government's R&D portfolio has shifted. Additional industry and expert interviews to validate or revise the previously used 6-year acceleration assumption would be valuable. Second, further validation or revision of the assumption that 80% of the impacts are attributable to public funding (vs. industry cost-share of that public funding) also has merit. Third, additional effort could further improve the representation of air emissions health benefits. Specifically, as federal guidelines for the treatment of carbon emissions reductions come into focus, it may be warranted to monetize the benefits of these reductions. Fourth, other possible societal benefits not covered in the present work might also be assessed. Finally, the estimates presented for a U.S.-based two-factor learning curve are imprecise, and they lack strong statistical significance or model stability. Future work could seek to improve this two-factor learning curve model by including additional possible explanatory variables (e.g., steel prices, currency movements), testing additional knowledge depreciation and lag assumptions, incorporating interaction terms, considering private R&D investments, and/or assessing other possible improvements to the statistical model.

In addition to further validating and improving the numerical economic estimates presented in this paper, completely different types of research are needed to better judge what specific wind R&D investments are most likely to yield the greatest positive returns. Should wind R&D focus on land-based or offshore technologies? What specific scientific and technical challenges ought to be tackled with public R&D? The present analysis was performed at an aggregate, portfolio level, so it does not answer these important questions. To inform investment strategies, detailed evaluations of past targets of wind R&D would be helpful—revealing what specific R&D efforts have worked well and which have not. Close engagement with and reviews from the private sector will likely remain essential to these efforts, as will collaborations with R&D institutions around the world given the now-global scale of the wind sector.

The basic analytical approaches refined and employed in this paper are applicable to a broad array of energy R&D investments, not just wind. Applying the methods more broadly and in as comparable a

fashion as possible to many energy technologies—such as solar, biomass, geothermal, natural gas, coal, nuclear, and energy efficiency—would help policymakers judge the relative success of R&D investments across the full technology portfolio. Some adjustments to the approach would likely be needed when applied beyond wind, to reflect unique, technology-specific details. Nonetheless, the present analysis suggests several areas of focus for further assessments. First, given the importance of the acceleration, attribution, and useful-life assumptions, a common set of standardized methods would ideally be employed to estimate these parameters for each technology assessed. Second, because of the sensitivity of the results to discount rates, future analyses would benefit from further considering appropriate discounting practices. Third, comprehensive and defensible underlying data on cost, deployment, and other factors are essential to these evaluations, and more effort may be needed to ensure adequate tracking of such details. Fourth, all quantifiable benefits and costs should be included in such assessments; where benefits or costs cannot easily be monetized, they should be described. Finally, the current paper includes novel use of two-factor learning curves to assess the impacts of R&D on technology costs and develop R&D net-return performance measures. While there are limitations to this method, it offers a useful benchmark for the core analysis approach. Work to refine this basic method is justified, to assess whether it might have wider applications in other R&D assessments. Whether or not two-factor learning curves are applied, comprehensive sensitivity analyses are warranted to clarify the robustness of the resulting economic-return estimates.

CRedit authorship contribution statement

Ryan Wiser: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Validation, Writing - original draft, Writing - review & editing. **Dev Millstein:** Data curation, Formal analysis, Methodology, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The work described in this study was supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231. The U.S. Government retains, and the publisher, by accepting the article for publication, acknowledges, that the U.S. Government retains a non-exclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for U.S. Government purposes. For their contributions to and/or review of this work, the authors thank Richard Tusing, Garrett Barter, and Eric Lantz (National Renewable Energy Laboratory); Mark Bolinger (Lawrence Berkeley National Laboratory); Patrick Gilman, Valerie Reed, Steve Capanna, Sam Baldwin, and Jeff Dowd (U.S. Department of Energy); and Ed DeMeo (Renewable Energy Consulting Services, Inc.). Additional comments were graciously provided by a number of external reviewers. Note that the data and analysis underlying this report are available via reasonable request to the authors.

Appendix A. Summary of subset of key analytic input parameters

Year	DOE wind energy R&D budget (million, real 2017\$)*	Land-based wind LCOE (real 2017\$/MWh)**	U.S. wind power capacity additions (GW)***
1974	0	909	na
1975	0	858	na
1976	49	807	na
1977	72	756	na
1978	111	705	na
1979	166	654	na
1980	155	604	na
1981	181	553	0.0
1982	76	502	0.1
1983	66	451	0.2
1984	54	400	0.4
1985	56	349	0.4
1986	48	310	0.2
1987	31	270	0.1
1988	16	242	0.0
1989	15	213	0.0
1990	15	185	0.1
1991	18	165	0.1
1992	34	145	0.0
1993	38	125	0.0
1994	47	114	0.0
1995	68	109	0.0
1996	46	104	0.0
1997	42	99	0.0
1998	46	94	0.1
1999	48	89	0.9
2000	44	80	0.1
2001	54	75	1.7
2002	51	73	0.4
2003	54	71	1.7
2004	51	68	0.4
2005	50	66	2.4
2006	46	65	2.5
2007	57	63	5.3
2008	56	62	8.4
2009	61	61	10.0
2010	89	59	5.2
2011	87	58	6.6
2012	99	57	13.3
2013	91	56	1.1
2014	92	54	4.9
2015	110	50	8.6
2016	97	46	8.2
2017	90	47	7.0

*DOE program management costs are assumed to add 8% to these annual figures, based on DOE Office of Energy Efficiency and Renewable Energy (EERE) budgets for 2014–2017 (https://www5.eere.energy.gov/office_eere/program_budget_formulation.php). This covers DOE staff and management costs and assumes proportional allocation of those costs across all DOE EERE program areas.

**Historical land-based wind LCOE derives from data in DOE [31] and Wiser and Bolinger [11], with interpolation to “smooth” the data from 1995 to 2013.

***Historical U.S. wind power capacity data come from various versions of the U.S. DOE Wind Technologies Market Report: <https://emp.lbl.gov/wind-technologies-market-report>.

Appendix B. Detailed summary of analysis results

	Pelsoci Extension, 6- year LCOE & Deployment Acceleration, with EUL (base case)	Pelsoci Extension, 4- year LCOE & Deployment Acceleration, with EUL (sensi- tivity)	Pelsoci Extension, 8- year LCOE & Deployment Acceleration, with EUL (sensi- tivity)	Pelsoci Extension, 6- year LCOE- only Acceleration, with EUL (al- ternative)	Pelsoci Extension, 4- year LCOE- only Acceleration, with EUL (sen- sitivity)	Pelsoci Extension, 8- year LCOE- only Acceleration, with EUL (sen- sitivity)	2-Factor Learning Curve, Literature Review-Shift (alternative)	2-Factor Learning Curve, Literature Review-LBR (alternative)	2-Factor Learning Curve, Own Estimates-LBR (alternative)
R&D performance period	1976–2017, EUL to 2042	1976–2017, EUL to 2042	1976–2017, EUL to 2042	1976–2017, EUL to 2042	1976–2017, EUL to 2042	1976–2017, EUL to 2042	1976–2017, EUL to 2042	1976–2017, EUL to 2042	1976–2017, EUL to 2042
Assumed effect	LCOE and de- ployment accel- eration	LCOE and de- ployment accel- eration	LCOE and de- ployment accel- eration	Only LCOE ac- celeration	Only LCOE ac- celeration	Only LCOE ac- celeration	Only LCOE reduction	Only LCOE reduction	Only LCOE re- duction
Benefits included	Energy cost & health benefits	Energy cost & health benefits	Energy cost & health benefits	Only energy cost benefits	Only energy cost benefits	Only energy cost benefits	Only energy cost benefits	Only energy cost benefits	Only energy cost benefits
R&D cost (undis- counted)	\$3.0 Billion	\$3.0 Billion	\$3.0 Billion	\$3.0 Billion	\$3.0 Billion	\$3.0 Billion	\$3.0 Billion	\$3.0 Billion	\$3.3 Billion

R&D cost at 3%	\$1.7 Billion	\$1.7 Billion	\$1.7 Billion	\$1.7 Billion	\$1.7 Billion	\$1.7 Billion	\$1.7 Billion	\$1.7 Billion	\$1.7 Billion
R&D cost at 7%	\$1.1 Billion	\$1.1 Billion	\$1.1 Billion	\$1.1 Billion	\$1.1 Billion	\$1.1 Billion	\$1.1 Billion	\$1.1 Billion	\$1.1 Billion
Benefits (undiscounted)	\$116.6 Billion	\$92.4 Billion	\$134.1 Billion	\$66.1 Billion	\$43.4 Billion	\$94.6 Billion	\$55.2 Billion	\$41.8 Billion	\$103.2 Billion
Benefits at 3%	\$33.1 Billion	\$26.3 Billion	\$37.8 Billion	\$21.1 Billion	\$13.6 Billion	\$30.4 Billion	\$15.0 Billion	\$12.1 Billion	\$30.0 Billion
Benefits at 7%	\$7.5 Billion	\$6.0 Billion	\$8.3 Billion	\$6.2 Billion	\$3.9 Billion	\$8.8 Billion	\$3.2 Billion	\$2.9 Billion	\$7.2 Billion
Net benefits (undiscounted)	\$113.6 Billion	\$89.4 Billion	\$131.1 Billion	\$63.1 Billion	\$40.4 Billion	\$91.6 Billion	\$52.2 Billion	\$38.8 Billion	\$100.2 Billion
NPV at 3%	\$31.4 Billion	\$24.5 Billion	\$36.1 Billion	\$19.4 Billion	\$11.9 Billion	\$28.7 Billion	\$13.3 Billion	\$10.3 Billion	\$28.2 Billion
NPV at 7%	\$6.4 Billion	\$5.0 Billion	\$7.3 Billion	\$5.1 Billion	\$2.9 Billion	\$7.7 Billion	\$2.1 Billion	\$1.8 Billion	\$6.1 Billion
BCR (undiscounted)	38 to 1	30 to 1	44 to 1	22 to 1	14 to 1	32 to 1	18 to 1	14 to 1	34 to 1
BCR at 3%	18 to 1	14 to 1	21 to 1	12 to 1	8 to 1	18 to 1	9 to 1	7 to 1	17 to 1
BCR at 7%	6 to 1	5 to 1	7 to 1	6 to 1	4 to 1	8 to 1	3 to 1	3 to 1	7 to 1
Carbon reduction	1510 million metric tons CO ₂	1120 million metric tons CO ₂	1790 million metric tons CO ₂	n/a	n/a	n/a	n/a	n/a	n/a

Note: All dollars are expressed in real 2017 terms.

References

- [1] Fouquet R. Historical energy transitions: Speed, prices and system transformation. *Energy Res Social Sci* 2016;22:7–12.
- [2] IPCC. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Farahani E, Kadner S, Seyboth K, Adler A, Baum I, Brunner S, Eickemeier P, Kriemann B, Savolainen J, Schlömer S, von Stechow C, Zwickel T, Minx JC, editor. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press; 2014.
- [3] Gallagher KS, Holdren JP, Sagar AD. Energy-technology innovation. *Annu Rev Environ Resour* 2006;31:193–237.
- [4] Nemet G, Kammen K. U.S. energy research and development: Declining investment, increasing need, and the feasibility of expansion. *Energy Policy* 2007;35:746–55.
- [5] PCAST. Federal energy research and development for the challenges of the 21st Century. Washington, DC: Office of Science and Technology Policy; 1997.
- [6] Arrow KJ. Economic welfare and the allocation of resources for invention. The rate and direction of inventive activity. Princeton, NJ: Princeton University Press; 1962.
- [7] Jaffe AB. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *Am Econ Rev* 1986;76:984–1001.
- [8] Cohen LR, Noll RG. The technology pork barrel. Washington, DC: The Brookings Institution Press; 1991.
- [9] Ford MJ, Abdulla A, Morgan MG, Victor DG. Expert assessments of the state of U.S. advanced fission innovation. *Energy Policy* 2017;108:194–200.
- [10] GWEC. Global wind report 2019. Brussels, Belgium: Global Wind Energy Council; 2019.
- [11] Wiser R, Bolinger M. 2017 Wind Technologies Market Report. Washington, D.C.: U.S. Department of Energy; 2018.
- [12] IRENA. Renewable power generation costs in 2017. International Renewable Energy Agency; 2018.
- [13] Veers P, Dykes K, Lantz E, Barth S, Bottasso CL, Carlson O, et al. Grand challenges in the science of wind energy. *Science* 2019. <https://doi.org/10.1126/science.aau2027>.
- [14] Wiser R, Yang Z, Hand M, Hohmeyer O, Infield D, Jensen PH, et al. Wind Energy. In: Edenhofer O, editor. IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Cambridge University Press; 2011.
- [15] Barthelmie RJ, Pryor SC. Potential contribution of wind energy to climate change mitigation. *Nat Clim Change* 2014;4:684–8.
- [16] MacDonald A, Clack C, Alexander A, Dunbar A, Wilczak J, Xie Y. Future cost-competitive electricity systems and their impact on US CO₂ emissions. *Nat Clim Change* 2016;6:526–31.
- [17] Zhang X, Ma C, Song X, Zhiy Y, Chen W. The impacts of wind technology advancement on future global energy. *Appl Energy* 2016;184:1033–7.
- [18] IEA. RD&D online data service. Paris, France: International Energy Agency; 2018.
- [19] Energy research at DOE: Was It Worth It? Energy Efficiency and Fossil Energy Research 1978 to 2000. Washington, DC: National Research Council; 2001.
- [20] Pelsoci TM. Retrospective benefit-cost evaluation of U.S. DOE wind energy R&D program: impact of selected energy technology investments. Washington, D.C.: U.S. Department of Energy; 2010.
- [21] Ruegg R, O'Connor AC, Loomis RJ. Evaluating realized impacts of DOE/EERE R&D programs. Washington, D.C.: U.S. Department of Energy; 2014.
- [22] Ruegg R, Thomas P. Linkages from DOE's wind energy program R&D to commercial renewable power generation. Washington, D.C.: U.S. Department of Energy; 2009.
- [23] Navigant. Impact and process evaluation of the U.S. Department of Energy's wind powering America initiative. Washington, D.C.: U.S. Department of Energy; 2013.
- [24] Hendry C, Harborne P. Changing the view of wind power development: More than 'bricolage'. *Res Policy* 2011;40:778–89.
- [25] Karnøe P. Technological innovation and industrial organization in the Danish wind industry. *Entrepreneurship Regional Dev* 1990;2:105–23.
- [26] Loiter JM, Norberg-Bohm V. Technology policy and renewable energy: public roles in the development of new energy technologies. *Energy Policy* 1999;27:85–97.
- [27] Lindman Å, Söderholm P. Wind power learning rates: a conceptual review and meta-analysis. *Energy Econ* 2012;34:754–61.
- [28] Rubin ES, Azevedo I, Jaramillo P, Yeh S. A review of learning rates for electricity supply technologies. *Energy Policy* 2015;86:198–218.
- [29] Ruegg R, Jordan G. Guidelines for conducting EERE retrospective benefit-cost studies. Washington, D.C.: U.S. Department of Energy; 2009.
- [30] Millstein D, Wiser R, Bolinger M, Barbose G. The climate and air-quality benefits of wind and solar power in the United States. *Nat Energy* 2017;2:17134.
- [31] DOE. Revolution...Now: The Future Arrives for Five Clean Energy Technologies–2016 Update. Washington, D.C.: U.S. Department of Energy; 2016.
- [32] Mone C, Hand M, Bolinger M, Rand J, Heimiller D, Ho J. 2015 cost of wind energy review. Golden, Colorado: National Renewable Energy Laboratory; 2017.
- [33] OMB. Circular A-94. Washington, D.C. Office of Management and Budget; 1992.
- [34] OMB. Circular A-4. Washington, D.C. Office of Management and Budget; 2013.
- [35] Samadi S. The experience curve theory and its application in the field of electricity generation technologies – A literature review. *Renew Sustain Energy Rev* 2018;82:2346–64.
- [36] Wiser R, Jenni K, Seel J, Baker E, Hand M, Lantz E, et al. Expert elicitation survey on future wind energy costs. *Nat Energy* 2016;1:16135.
- [37] Williams E, Hittinger E, Carvalho R, Williams R. Wind power costs expected to decrease due to technological progress. *Energy Policy* 2017;106:427–35.
- [38] Junginger M, Hittinger E, Williams E, Wiser R. Onshore wind energy. Chapter 6 in Junginger M, Louwen A, editors. Technological Learning in the Transition to a Low-Carbon Energy System. Elsevier; 2020.
- [39] Ek K, Söderholm P. Technology learning in the presence of public R&D: The case of European wind power. *Ecol Econ* 2010;69:2356–62.
- [40] Yeh S, Rubin ES. A review of uncertainties in technology experience curves. *Energy Econ* 2012;34:762–71.
- [41] Wiesenthal T, Dowling P, Morbee J, Thiel C, Schade B, Russ P, et al. Technology learning curves for energy policy support. European Commission Joint Research Centre; 2012.
- [42] Wiesenthal T, Mercier A, Schade B, Petric H, Dowling P. A model-based assessment of the impact of revitalised R&D investments on the European power sector. *Renew Sustain Energy Rev* 2012;16:105–12.
- [43] Yu Y, Li H, Che Y, Zheng Q. The price evolution of wind turbines in China: A study based on the modified multi-factor learning curve. *Renew Energy* 2017;103:522–36.
- [44] Wiebe K, Lutz C. Endogenous technological change and the policy mix in renewable power generation. *Renew Sustain Energy Rev* 2016;60:739–51.
- [45] Miketa A, Schratzenholzer L. Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes: first results. *Energy Policy* 2004;32:1679–92.
- [46] Kobos PH, Erickson JD, Drennen TE. Technological learning and renewable energy costs: implications for US renewable energy policy. *Energy Policy* 2006;34:1645–58.
- [47] Jamasb T. Technical change theory and learning curves: patterns of progress in electricity generation technologies. *Energy J* 2007;28:51–71.
- [48] Söderholm P, Sundqvist T. Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies. *Renew Energy* 2007;32:2259–578.
- [49] Söderholm P, Klaassen G. Wind power in Europe: a simultaneous innovation-diffusion model. *Environ Resour Econ* 2007;36:163–90.
- [50] Klaassen G, Miketa A, Larsen K, Sundqvist T. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. *Ecol Econ* 2005;54:227–40.
- [51] Goff C. Wind energy cost reductions: a learning curve analysis with evidence from the United States, Germany, Denmark, Spain, and the United Kingdom. Thesis submitted to Georgetown University. Washington, D.C.; 2006.
- [52] Grafström J, Lindman Å. Invention, innovation and diffusion in the European wind power sector. *Technol Forecast Soc Chang* 2017;114:179–91.
- [53] Cory K, Bernow S, Dougherty W, Kartha S, Williams E. Analysis of wind turbine cost reductions: the role of research and development and cumulative production. Presented at: AWEA's WINDPOWER '99 Conference. Burlington, Vermont; 1999.
- [54] Kahouli-Brahmi S. Technological learning in energy–environment–economy modelling: A survey. *Energy Policy* 2008;36:138–62.
- [55] van Kuik G, Peinke J, Nijssen R, Lekou D, Mann J, Sorensen JN, et al. Long-term research challenges in wind energy – a research agenda by the European Academy of Wind Energy. *Wind Energy Sci* 2016;1:1–39.